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Abstract: A comprehensive understanding of individual-level discounting behaviours is crucial because of its implications for designing financial incentive interventions encouraging health behaviors. This paper estimates mixture models to determine probabilistically the discounting functional form which has the best fit to discounting behaviours, on the basis of a series of incentive-compatible time and risk preference field experiments conducted among 176 civil servants in Belfast, Northern Ireland. Time preference was structurally estimated while controlling for risk preference, background consumption, and probability weighting. The results suggested that future monetary incentives were discounted hyperbolically rather than exponentially and that a generalised hyperbolic form had the best fit among a series of alternative functional forms. Our results also showed that the failure to adopt an appropriate type of functional form led to significantly different discount rates and misleading associations between time preference and real-world behaviours such as smoking. Identifying the best-fit discounting functional form may be a useful tool to improve the effectiveness of financial incentive interventions such that more immediate rewards should be provided to the target population with a higher degree of time-inconsistency.

Keywords: Hyperbolic discounting; Time preference; Risk preference; Mixture models; Smoking

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1 Introduction

People often face choices in which they must trade-off an immediate, smaller versus a later, higher gratification. Psychologists and behavioural economists have discovered that humans tend to devalue a delayed reward so that the subjective value is higher for an immediate reward of the same nominal amount (Frederick, Loewenstein, & O'Donoghue, 2002; Kirby & Marakovic, 1996). This trait is denoted as time preference, which is also known as delay discounting or temporal discounting. The extent to which future reward is discounted is represented by the discount rate. There is a rich literature on the association between discount rates and various impulsive unhealthy behaviours (Courtemanche, Heutel, & McAlvanah, 2015; Harrison, Lau, & Rutstrom, 2010; Ikeda, Kang, & Ohtake, 2010; Kang & Ikeda, 2014; MacKillop et al., 2011; Reynolds, 2006; Richards & Hamilton, 2012; Story, Vlaev, Seymour, Darzi, & Dolan, 2014). Since policy makers are paying increasing attention to the use of financial incentives in behavioural change programs, for example, to encourage smoking cessation (Volpp et al., 2008) and physical activity (Patel et al., 2016), a better understanding of how financial incentives are discounted would be useful to shed light on the type of incentivised programmes that might be most valuable for encouraging health behaviours in specific population groups. Tailoring these interventions based on the nature of time preferences has the potential to improve their effectiveness, especially in cases where financial incentives are awarded in the future after health targets are achieved e.g. commitment contracts (Loewenstein, Asch, Friedman, Melichar, & Volpp, 2012).

It is becoming increasingly popular among health economists to elicit time preferences (discount rates) by conducting field experiments composed of a series of incentive-compatible real-stake choices tasks (Andersen, Harrison, Lau, & Rutstrom, 2008, 2014; Andreoni, Kuhn, & Sprenger, 2015; Freeman, Manzini, Mariotti, & Mittone, 2016)[1]. To represent how future

[1] An alternative method to measure time preference is by asking participants to imagine a hypothetical illness and to choose between immediate over delayed occurrence of the illness (Van der Pol & Cairns, 2011). However, after

rewards are evaluated and discounted, a functional form for discounting must be assumed. However, there is no consensus on which parametric form most accurately characterises discounting behaviours. First, it is difficult to draw firm conclusions from previous literature on whether future incentives are discounted to their present values exponentially or hyperbolically in incentive-compatible environments. For instance, Harrison and Lau (2005) argued that hyperbolic discounting is an "experimental artefact" because a majority of experiments fail to control for credibility of future payments so that subjects always choose the immediate payments, causing hyperbolical intertemporal preferences. Kirby and Santiesteban (2003) asserted that any affirmation of hyperbolic discounting is confounded when a concave utility function is assumed to be linear. When a front-end delay (FED) is imposed to ensure equal credibility of sooner and later payments and risk preference is controlled to account for concavity of the utility function, Andersen et al. (2008) found that 93% of observations reflected exponential discounting while hyperbolic discounting accounted for only 7%. Further, Andersen et al. (2014) again found no support for hyperbolic discounting in a sample of 413 Danish adults. A similar finding was reported by Andreoni and Sprenger (2012) for a group of 249 American undergraduate students. Conversely, Harrison, Hofmeyr, Ross, and Swarthout (2017) observed hyperbolic discounting in a group of 175 South African students using similar methods[2]. Because of these contradictory findings, more evidence is needed before any conclusions can be reached. Secondly, little insight exists into which candidate functional form most accurately describes intertemporal preferences. Researchers have frequently made arbitrary choices as to the discounting functional form when analysing behavioural data by assuming exponential discounting (Booij & van Praag, 2009; Coller, Harrison, & Rutstrom, 2012), Mazur hyperbolic discounting (Chabris, Laibson, Morris, Schuldt, & Taubinsky, 2008;

reviewing the time preference studies that have used hypothetical health, Story et al. (2014) argued that the time preference elicited by this method suffer from hypothetical bias and thus not recommended.

[2] In a non-monetary context, McDonald et al. (2017) observed non-exponential discounting for students' intertemporal choices involving mortality risks.

Dasgupta & Maskin, 2005), or Quasi-hyperbolic discounting (Burks, Carpenter, Gotte, & Rustichini, 2012; Courtemanche et al., 2015; Ida, 2014; Salanie & Treich, 2006). As argued by Luhmann (2013), it is crucial to distinguish among different types of hyperbolic discounting because the widely used hyperbolic specifications in psychological studies, such as the *Mazur* specification, do not necessarily characterise discounting behaviours. Even the Quasi-hyperbolic model prominent among economists did not capture intertemporal preferences (Abdellaoui, Attema, & Bleichrodt, 2010).

A number of studies have attemped to discriminate among discounting funtional forms. Proxy measures were constructed to indicate hyperbolic discounting if the relative discount rate between two proximal dates is higher than the relative discount rate between two distal dates with the same length of delay (Ikeda et al., 2010; Kang & Ikeda, 2014). This parsimonious dummy indicator approach is limited because it does not quantify the magnitude of the hyperbolic discount rate. Other studies were limited to comparing model-fit assessed by the sum of squared errors (Abdellaoui et al., 2010; McKerchar et al., 2009; Ohmura, Takahashi, & Kitamura, 2005; Richards & Hamilton, 2012; Stillwell & Tunney, 2012) or by the Akaike Information Criterion (Abdellaoui, Bleichrodt, & l'Haridon, 2013). Cavagnaro, Aranovich, McClure, Pitt, and Myung (2016) used a simulation method based on laboratory experiment data but did not control for risk preference which leads to upward-biased discount rate estimates as put forward by Andersen et al. (2008). In our paper, we probabistically discriminate among alternative discounting functions by mixture models based on a series of economic experiments which: (i) use real payments; (ii) control for credibility of future payment by imposing a front-end delay, (iii) control for concavity of the utility function; and (iv) control for background information and probability weighting.

The contributions of the paper are threefold. First, we establish the usefulness of a mixture model, and indeed fully exploit its potential by controlling for elements such as risk preference, background consumption and probability weighting which are often ignored in the literature but may affect estimation of discount rates. Second, our study is among the first to show that the failure to adopt an appropriate type of functional form can lead to significantly different discount rates and misleading associations between time preference and real-world behaviours such as smoking. The third merit is that the field experiments were conducted on a unique population-based sample with real payments, offering more credibility for the validity of our results. In the study to be reported here, we are able to establish the nature of discounting behaviour in the sample from the data itself. A majority of economic experiments studies were conducted with university students who are easily accessible but may limit the value in informing public health policies.

The structure of the paper is as follows. Section 2 presents the experimental design and Section 3 shows the methodology and estimation framework. Section 4 describes the sample and dataset. Section 5 presents empirical results and Section 6 concludes.

2 Experimental design

We apply the multiple price lists (MPL) design in which participants were presented with a table with ten ordered dichotomous choices (one per row) and asked to indicate one answer for each row. Coller and Williams (1999) were the pioneers of MPL to elicit discount rates, which were then popularized by Holt and Laury (2002) and Andersen et al. (2008, 2014). A landmark paper in the discount rate elicitation literature is Andersen et al. (2008) who demonstrated that discount rate MPL should be “corrected” by considering parallel risk preference tasks in order to avoid upward-biased discount rate estimates. In light of this, in our design, participants were presented with both time preference and risk preference MPLs.

2.1 Time preference MPLs

Each time preference MPL had 10 choice tasks, each of which had two outcomes: a smaller immediate reward (Option *A*; £250) and a larger future reward which varied according to the length of the time horizon (Option *B*) (see Appendix Table 1 for an example). The future reward for the first choice task was obtained by incrementing the principal (£250[3]) by an annual rate of 5%, which increases by the conventional 5% as it progresses to the next choice task, reaching 50% for the last (10th) choice task. The information on annual effective interest rates was shown on the MPLs. A multiple-horizon treatment was used and these were randomly drawn from the six time horizons: 1, 2, 3, 4, 5, and 6 months. The three chosen time horizons (in a random order) were presented with a one-month FED (Front End Delay[4]) and non-FED, respectively, leading to six MPLs for each participant. Before proceeding to the formal MPLs, the participants were asked to practice an example MPL. A participant was expected to choose Option *A* for the first several choices and switch to Option *B* at some point. The switching point determines the participant's discount rate. For instance, if a participant chooses Option *A*, say, for the first four tasks (corresponding to a discount rate of 20%) and Option *B* from the fifth and subsequent tasks (corresponding to a discount rate of 25%), it can be inferred that the individual discount rate for the participant is between 20%-25%.[5] If Option *A* is chosen for all 10 tasks, it indicates a highly impatient participant who has a discount rate higher than 50%, because the £250 principle is still chosen even when the future reward is larger than the principle by a 50% interest rate. Similarly, another extreme case is when Option *B* is chosen for all tasks, which indicates a discount rate below 5%.

2.2 Risk preference MPLs

Similar to the time preference MPL, the risk preference MPL (see Appendix Table 2) also has two options *A* and *B*. Each of the two options gives two alternative rewards, e.g. £140 and £80

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[3] The £250 principle is comparable to the amount used in other developed societies, for instance Denmark (Andersen et al., 2014).

[4] The one-month front-end delay indicates a one-month delay on both the early and late payments to control for the transaction costs possibly associated with future payments, such as the credibility of being paid (Andersen et al., 2008).

[5] Another method to elicit time preference estimates is to calculate the mean of the six discount rates inferred from the switching points in the six MPLs (Ikeda et al., 2010). However, this method suffers from an upward-bias because it assumes neutral risk preference which is often violated (Andersen et al., 2008).

(Option *A*) and £200 and £20 (Option *B*). The probabilities of getting the *A* or *B* rewards are identical in both options. Option *A* in choice task 1 gives a 10% chance of receiving £140 and 90% chance of receiving £80 while Option *B* has a 10% chance of getting a significantly higher amount (£200) and 90% of getting a much lower amount (£20). Thus, Option *A* is a "safe" option since the least possible reward is £80, as compared to "risky" Option *B* where there is a small chance of getting £200 but a large chance of getting only £20. As the participant moves down from one task to the next, the chance of receiving the larger (lower) amounts in both lotteries increases (decreases) by 10%. In other words, Option *B* gradually becomes a "safer" choice as the tasks progress down. The "safeness" of Option *B* as opposed to Option *A* is manifested by the differences between the expected values of the two options, which are negative in the first 4 tasks, 0 in the fifth task, and positive in tasks 6-10. Again the switching point determines an individual's risk preference. A risk-loving participant would switch before the fifth task and risk for the higher reward (£200), despite the expected value of Option *B* for the first four tasks being lower than that of Option *A*. A risk-averse participant would switch after the fifth task, although Option *B* (compared to those after the fifth) has a higher expected value, to avoid the possibility (despite small) of getting a lower reward of £20. A risk neutral decision-maker will switch at choice task 5.

3 Methodology

3.1 Econometric framework

We turn to the methodology of eliciting time and risk preferences based on the MPLs described in Section 2. Following Andersen et al. (2008) and the literature thereafter, we control for a concave utility function, since the failure to comply leads to upward-biased discount rate estimates. We also control for probability weighting which is frequently neglected which refers to the phenomenon that individuals tend to make decisions under uncertainty based on objective rather than subjective probabilities (Tversky & Kahneman, 1992). Put differently, people often form differentiated objective or personal probabilities when presented with the same physical probabilities. Not controlling for probability weighting has resulted in different discount rate estimates (Laury, McInnes, & Swarthout, 2012). Furthermore, to understand which discount functional form better describes the data, we estimate mixture models which provide a robust and reliable classification of individuals into one functional form against its alternatives. Greater details on the specification of the econometric framework are provided in Appendix 3.

3.2 Time preference functional forms

We do not intend to consider all existing functional forms in the time preference literature[6], but instead to include only the most prominent functional forms listed in Andersen et al. (2014). We consider two sole-parameter specifications (*Exponential* and *Mazur*) and three dual-parameter specifications (*Weibull*, *Quasi-hyperbolic*, and *General-hyperbolic*), where the former quantifies the level of impatience by its sole-parameter, and the latter accommodates the two facets of time preference, namely impatience (the magnitude of a general discount rate) and time-inconsistency (the trend that discount rate decreases with time). The two facets are independent so that highly impatient individuals may have either time-consistent or -inconsistent discounting. As we will show later, disentangling the two should help us to devise incentive strategies that fit the discounting patterns of a target population.

Samuelson's (1938) *Exponential* specification has a constant discount rate which is defined as follows:

$$DR_{(E)} = \delta^E \tag{1}$$

where δ^E represents the *Exponential* discount rate which is constant over time. Its discount factor $DF_{(E)}$ equals $1/(1+\delta^E)^t$.

Mazur's (1984) functional form assumes that the discount rate is:

$$DR_{(M)} = (1+\delta^K t)^{1/t} - 1 \tag{2}$$

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[6] For a survey of functional forms see Abdellaoui et al. (2010) and Rohde (2010).

where t indicates time horizon and δ^K is a parameter to be estimated. Similar to *Exponential*, the discount factor for *Mazur* is $DF_{(M)} = 1/(1+\delta^K t)$.

Read's (2001) *Weibull* specification has discount rates represented as:

$$DR_{(WB)} = exp(\delta^{WB} t^{(1-\beta^{WB})/\beta^{WB}}) - 1 \qquad (3)$$

where t is time horizon, δ^{WB} a parameter determining the level of discount rate, and β^{WB} an indicator of a declining discount rate over time. Transforming (3), *Weibull*'s discount factor is obtained: $DF_{(WB)} = exp(-\delta^{WB} t^{1/\beta^{WB}})$. If β^{WB} is close to 1, $DF_{(WB)}$ collapses to $\exp(-\delta^{WB} t)$, the exponential discounting form. If β^{WB} is larger than 1, it takes the shape of a hyperbolic function.

Next, the discount rates for Laibson's (1997) *Quasi-hyperbolic* specification are defined as:

$$DR_{(QH)} = [\beta^{QH}/(1+\delta^{QH})^t]^{-1/t} - 1 \qquad (4)$$

with a discount factor of $[\beta^{QH}/(1+\delta^{QH})^t]$ where β^{QH} is an indicator for time-inconsistency and δ^{QH} the level of long-term discount rates. $\beta^{QH} < 1$ implies time-inconsistent discounting whereas $\beta^{QH} = 1$ indicates exponential discounting.

Finally, Loewenstein and Prelec's (1992) *General-hyperbolic* specification has its discount rates defined as:

$$DR_{(GH)} = (1+\beta^{GH} t)^{\frac{\delta^{GH}}{\beta^{GH} t}} - 1 \qquad (5)$$

where δ^{GH} and β^{GH} determine the level of discount rate and the extent of time-inconsistency, respectively. The implied discounting factor for this specification is $DF_{(GH)} = 1/(1+\beta^{GH} t)^{\frac{\delta^{GH}}{\beta^{GH}}}$. If β^{GH} is close to 1, Eq. (5) collapses to the exponential discount function. If β^{GH}>1, the discount rates decrease over time. The magnitude of β^{GH} determines the speed of the declining trend. One should note that δ and β are independent so that impatient individuals (high δ) may display either time-consistent or time-inconsistent discounting.

The estimations followed a three-step procedure. First, the five discount factor specifications ($DF_{(E)}$, $DF_{(M)}$, $DF_{(WB)}$, $DF_{(QH)}$ and $DF_{(GH)}$) were individually inserted into the econometric framework described in Appendix 3 to estimate their corresponding shape parameters. Next, four mixture models (*General-hyperbolic* versus *Exponential*; *General-hyperbolic* versus *Mazur*; *General-hyperbolic* versus *Weibull*; *General-hyperbolic* versus *Quasi-hyperbolic*) were estimated to discover the probabilities that choices belong to two alternative functional forms. Finally, the shape parameters from the five discounting models were allowed to be heterogeneous across smoking status within the same maximum likelihood estimation framework to estimate the marginal effects of smoking status on the shape parameters. All models control for risk preference, probability weighting and background consumption.

4 Sample

The field experiments were conducted in February 2013 in Belfast, Northern Ireland, as a part of the Physical Activity Loyalty (PAL) card scheme (for a detailed description of the scheme see (Hunter, Tully, Davis, Stevenson, & Kee, 2013) which aimed at increasing workplace physical activity. 176 office-based civil servants took part in the experiments by responding to invitation emails which were sent to them via their internal network at work. Participants were randomised into groups of between 10 and 18. Prior to the experiments, the participants were informed that there was a 10% chance of getting their chosen rewards paid for real, independently for the discounting and risk tasks. Whether a participant received a reward from the discounting tasks was decided by rolling a 10-sided die, with the prize rewarded when number 1 was rolled. A 6-sided die and 10-sided die were then rolled to determine the number of the choice task and the question number to be paid. Participants' answers to that particular choice task determined the reward which was paid on the chosen date of payment. The payment for the risk preference task followed a separate and similar procedure where a 10-sided die was rolled to determine whether a reward from the risk preference task was to be received, and, if number 1 was rolled, another throw of a 10-sided die determined the number of the task to be played for real money. Each participant completed sixty time preference and ten risk preference choice tasks, amounting to 12,320 choices.

5 Empirical findings

5.1 Descriptions of choices

Figure 1 shows the distribution of choices from the discounting tasks with and without a FED. Each participant completed six time preference MPLs, amounting to a total of 1056. Among them, 93% had no multiple switches (switch from Option *A* to Option *B* then switch back to Option *A*), suggesting that a majority of the participants understood the tasks well [7]. Among the choices without multiple switches, only 3% were "never-switched" choices, i.e. Option *A* was selected for all 10 tasks, indicating that the upper-limit (50%) discount rate "covers" the discount rates of a majority of participants, irrespective of time horizons. Figure 1 shows that the proportion of participants choosing Option *B* (future payment) increases with the amount of future rewards. Imposing an FED did not lead to a different share of participants opting for Option *B*. This is surprising and contrasts with the results reported by Andersen et al. (2014). A possible explanation is that credibility of receiving future payments was guaranteed in this study so that the transaction costs associated with future payments were minimal.

[Insert Figure 1 about here]

5.2 Probability weighting

Table 1 shows the maximum likelihood estimations individually for the five discount functions while controlling for risk preference, background consumption and probability weighting. We

[7] Tanaka, Camerer, and Nguyen (2010) suggested enforcing monotonic switching by asking participants at which question they would like to switch. However, we did not follow this because "forcing" participants to switch may change their discount rates.

first discuss risk preference r and probability weighting parameters η and φ. The risk preference parameter r is estimated to be significantly different from zero in four of the five models: 0.57 (*Exponential*), 0.67 (*Weibull*), 0.60 (*Quasi-hyperbolic*) and 0.71 (*General-hyperbolic*)[8], which is in line with our expectation of a concave utility function. These figures are close to that of the Danish population (0.65, Andersen et al., 2014., page 22). φ has estimations significantly larger than 1 in all five models (2.48, *Exponential*; 2.45, *Mazur*; 2.47, *Weibull*; 2.48, *Quasi-hyperbolic*; 2.46, *General-hyperbolic*)[9], suggesting an S-shaped probability weighting function. The threshold probability is approximately 40%, below (above) which the probabilities are under-weighted (over-weighted). The estimation of η varies from 0.73 (*Mazur*) to 1.10 (*General-hyperbolic*). Figure 2 displays the implied S-shaped probability weighting functions for the five models. It can be observed that the shape of probability weighting function is robust across models.

[Insert Table 1 about here]

[Insert Figure 2 about here]

5.3 Exponential or hyperbolic discounting?

We first examine whether participants displayed exponential or hyperbolic discounting by observing the parameters describing time-inconsistency. The *Weibull* model aligns with hyperbolic discounting: the estimate of β^{WB} (1.29) is significantly larger than 1 (p<0.01). Its impatience parameter δ^{W} is 0.14, which is significantly different from 0 (p<0.01). Likewise, the β^{GH} parameter from the *General-hyperbolic* model is estimated to be 3.25 and is

[8] The *Mazur* model gives an estimate of 0.26 (p=0.12).
[9] A test for the null hypothesis φ=1 is rejected at the 1% significance level for all five models.

significantly larger than 1 (p<0.01), also indicating time-inconsistent discounting. Additionally, the *General-hyperbolic* discounting factor δ^{GH} has an estimate of 0.25. Again, the *Quasi-hyperbolic* model reveals an estimate of 0.993 for the time-inconsistency coefficient β^{QH}, which differs from 1, that would signify a constant discount rate (β^{QH}=1 rejected, p<0.01).

Figure 3 shows the predicted hyperbolic discount rates over time. The *Exponential* discount rates are time-invariant at 0.20. Relatively high discount rates implied by *Mazur* are observed: 31.1% for a 1-month horizon with only a small decrease to 27.5% for a 1-year horizon. Conversely, the *General-hyperbolic* discount rates show a smooth decline from 0.28 (1-week horizon) to 0.25 (1-month horizon), then to 0.20 (3-month horizon), and further to 0.12 for a 1-year horizon. *Weibull* discount rates have a deeper decline within the 1-month horizon, followed by decreases at a slower pace after that period. Similarly, the *Quasi-hyperbolic* rates show a rapid fall for short delay periods (30 days) but become smooth afterwards. The annualized discount rates are relatively high and indicate higher impatience compared to other populations, such as the Danish with a discount rate of 0.1 (Andersen et al., 2014).

[Insert Figure 3 about here]

5.4 *Weibull*, *Quasi-hyperbolic*, or *General-hyperbolic*?

It is shown in Section 5.3 that discount rates decrease with time by assuming one discount function. However, it is unclear which of the three specifications that permit time-inconsistency better describes the data and how robust the estimated discount rates are across different specifications. Goodness-of-fit assessment using Akaike's Information Criterion (AIC) reveals that *General-hyperbolic* (AIC=12793.3) has the best model fit, followed by *Weibull* (12857.56), *Quasi-hyperbolic* (12958.72), *Mazur* (12983.18), and *Exponential* (13033.66). Additionally, the noise parameter μ_D under *General-hyperbolic* is estimated to be 0.17, which is the smallest among all candidate functional forms: *Exponential* (0.38), *Mazur* (2.18), *Weibull* (0.22), and *Quasi-Hyperbolic* (0.22). This indicates that a better characterisation of a functional form for intertemporal choices suggests that fewer of these choices need be categorised as stochastic errors. Further, to explore the extent to which the five functional forms explain intertemporal preferences, we present in Table 2 a probabilistic characterization by estimating the following four mixture models: (*General-hyperbolic* vs. *Exponential*), and (*General-hyperbolic* vs. *Mazur*), (*General-hyperbolic* vs. *Weibull*) and (*General-hyperbolic* vs. *Quasi-hyperbolic*). The mixture probability for *General-hyperbolic*, π(*General-hyperbolic*), is 0.84 versus 0.16 for *Exponential*, suggesting that if *Exponential* was assumed to be the sole data generating process, the estimated discount rate would have been distorted for 84% of the choices. Instead, when both specifications are assumed, the choices of 84% of the subjects exhibit significant deviations from constant discounting. δ^{E}, $\delta^{GH}$and β^{GH} were estimated to be 0.17, 0.32 and 4.48, respectively, based on which the *General-hyperbolic* and *Exponential* discount rates across time horizons are predicted and shown in Appendix 4. It can be seen that hyperbolic discounters have higher discount rates than exponential discounters within the first 198 days. In a similar vein, *General-hyperbolic* is also found to have better quantitative representativeness than *Mazur*, since the individuals are assigned to *General-hyperbolic* with a probability of 76% and the remaining 24% allocated to *Mazur*. Furthermore, the mixture model of *General-hyperbolic* and *Weibull* shows that 77% choices can be characterized by *General-hyperbolic* (δ^{GH}=0.30; β^{GH}=3.50) and the rest 23% by *Weibull* (δ^{WB}=0.14; β^{WB}=1.29). Finally, the *General-hyperbolic* vs. *Quasi-hyperbolic* mixture model shows that 81% choices are attributed to *General-hyperbolic* and 19% to the *Quasi-hyperbolic* specification. It can be concluded that *General-hyperbolic* performs the best among the five specifications. Appendix 5 shows substantial discrepancies of discount rates for delayed time horizons between *General-hyperbolic* and the other superior-fit functional forms.

[Insert Table 2 about here]

5.5 Robustness to consumption smoothing, linear utility, and re-weighting

We now test whether our results implied in the mixture models would significantly change by altering three model settings. First, we allow consumption smoothing i.e. the prizes are consumed throughout the week following receipt, differing from the earlier where recipients are assumed to have consumed their cash prizes in one day. Second, we examine whether our results are robust to the assumption of linear utility. Third, given the fact that the number of time preference tasks is four times greater than the risk preference tasks, as an extra robustness check we re-weighted numerically the responses to the risk aversion tasks relative to the number of time preference tasks. The results for the three robustness checks are reported in Table 3. It can be seen that the probabilities for discounting behaviours characterised by *General-hyperbolic* against *Exponential* are robust under the risk-neutrality assumption (0.83) and re-weighting of risk preference tasks (0.83), although the figure (0.68) is lower when a week-long consumption period is assumed. Next, the *General-hyperbolic* vs. *Mazur* and *General-hyperbolic* vs. *Weibull* mixture models again suggested a substantial fraction (>0.72) of the subjects actually behaved according to *General-hyperbolic* as opposed to *Mazur* or *Weibull* (only minor differences in probabilities were found across models). Finally, the robustness checks for the models mixing *General-hyperbolic* and *Quasi-hyperbolic* also led to a preference for the former over the latter (the share of observed choices characterised by the former varied from 0.67 to 0.81). We thus conclude that the main findings drawn in Section 5.4 are robust to these modelling and specification choices.

[Insert Table 3 about here]

5.6 Allowing for heterogeneity of time preference across smoking status

Table 4 compares results from the five models when shape parameters are allowed to be heterogeneous across smoking status within the same maximum likelihood estimation framework. We use self-reported smoking status which is usually associated with high magnitude of impatience (Cawley & Price, 2013; Harrison et al., 2010; Ikeda et al., 2010; Khwaja, Silverman, & Sloan, 2007). The prevalence of current-smokers, ex-smokers, and never-smokers in the sample were 16.5%, 12.5% and 71.0%, respectively, consistent with the census data in Northern Ireland. When *General-hyperbolic* is assumed, the marginal effect of δ^{GH} (0.09, p<0.10) for *Smokers* is positive and significant, suggesting that smokers have generally higher discount rates than never-smokers. However, the marginal effects of *Smokers* on δ parameters become smaller and less significant under *Exponential* (0.04, p=0.15), *Mazur* (0.05, p=0.14), *Weibull* (0.02, p=0.26), and *Quasi-hyperbolic* (0.03, p=0.25). Likewise, compared to *Never-smokers*, *Ex-smokers* has significantly higher δ parameters assuming *Exponential* (0.05, p=0.06), *Mazur* (0.06, p=0.07), *Weibull* (0.03, p=0.07), and *Quasi-hyperbolic* (0.05, p=0.04), whereas the influence on δ^{GH}, the best-fit specification, is less significant (0.04, p=0.38). Thus, we conjecture that the failure to adopt an appropriate type of discount functional form may lead to significantly different estimates of discount rates and misleading associations between time preference and real-world behaviours. Next, the shape parameters ($\beta^{W}, \beta^{QH}, \beta^{GH}$) determining the time-inconsistency component of discounting do not seem to play much of a role: none of the marginal effects of *Smokers* and *Ex-smokers* are significant in any of the five models. This finding is in line with Harrison et al. (2017) who found that smoking status was not associated with the time-inconsistency of discount rates measured by similar incentivized experiments. Contradictory results are reported in Kang and Ikeda (2016) based on hypothetical time preference tasks while not controlling for risk preference. We conjecture that their conclusion may not hold under an incentivised and structured experimental setting like ours while correcting for concavity of utility function and controlling for other confounding factors, i.e. probability weighting and background consumption.

Due to these differentiated marginal effects of smoking status on the shape parameters, current-smokers, ex-smokers, and never-smokers manifested differentiated discount rates (shapes) when a different discounting specification is assumed (see Figure 4). Appendix 6-8 reports the differentiation of discount rates over time between *General-hyperbolic* and the poor-fit alternative specifications, respectively for current-smokers, ex-smokers, and never-smokers.

[Insert Table 4 about here]

[Insert Figure 4 about here]

5.5.3 Risk preference, probability weighting and unhealthy behaviours

We turn to the discussion of the association between smoking status and risk preference and subjective probability weighting. *Ex-smokers* has a negative and significant marginal effect on risk preference r, indicating that *Ex-smokers* are more risk-loving than *Never-smokers*. This trend is robust across models assuming different functional forms. On the contrary, *Smokers* exerts an insignificant effect on r, although with the expected negative signs. Additionally, *Ex-smokers* has a positive and significant effect on η, suggesting that *Ex-smokers* are more likely to over-weight large probabilities and under-weight smaller probabilities. Finally, we found no significant effect of smoking status, irrespective of the discounting specifications, on the probability weighting parameter φ, suggesting that *Smokers* and *Ex-smokers* do not necessarily have different subjective probabilities than their *Never-smokers* counterparts.

6. Discussion and Conclusions

The paper identifies the discount functional form which, probabilistically, has the best fit to discounting behaviours, based on economic experiments with real-payments conducted on a sample of 176 civil servants from Belfast, Northern Ireland. The experiments were composed of a series of multiple price lists to elicit time and risk preferences which were simultaneously estimated by a maximum likelihood method. A major contribution of this study is that it provides an empirical framework not only to parametrically discriminate between exponential and hyperbolic discounting, but also between three popular hyperbolic discounting specifications, namely *Weibull*, *Quasi-hyperbolic* and *General-hyperbolic* while controlling for risk preference, background consumption and probability weighting. The main implications are as follows.

First, the predicted shape parameters of the three dual-parameter specifications (*Weibull*, *Quasi-hyperbolic* and *General-hyperbolic*) unexceptionally indicate that hyperbolic discounting displayed descriptive superiority over exponential discounting in explaining the intertemporal choices made by participants, suggesting that the relative discount rate between two proximal dates is higher than the relative discount rate between two distal dates with the same length of delay. The fact that the dual-parameter discounting forms have superior fit over the sole-parameter functional forms accords with recent neuroeconomics theory, i.e. that there are competing neurobehavioral decision systems (CNDS) (Bickel et al., 2007; McClure, Laibson, Loewenstein, & Cohen, 2004), and that two distinct brain regions are involved in the discounting of delayed rewards, with one region associated with time-inconsistency (known as the impulsive decision system) and the other related to long-run discount rate (the executive decision system). According to CNDS theory, these decision systems are mutable under environmental manipulations, making time preference a fruitful target for intervention. The decomposition of time preference into its two components indicates that incentive strategies derived from each of the two elements differ such that discount rate determines the overall level of incentives whereas the time-inconsistency factor determines rewards immediacy. Discount rates were estimated to be approximately 0.25, which is higher than that of the Danish population (0.1). In the context of incentivised interventions encouraging health behaviors, the relatively high level of impatience suggests that a higher level of incentives is necessary for behavioural change. In addition, the results on time-inconsistency indicate that, for interventions where incentives have to be paid out when targets are met in the future, e.g. commitment contracts for smoking cessation, contracts that are shorter than 198 days will be more effective in getting exponential discounters started on the path to behaviour change than hyperbolic discounters who may require higher incentives during this period. Since hyperbolic discounters will almost certainly require higher initial incentives than exponential discounters to initiate behaviour change, possibilities may exist for designing novel commitment contracts which take advantage of the lower long-term discount rates of hyperbolic discounters, offering substantial and shorter term interim incentives or short-term penalties to initiate behaviour change coupled with smaller and long-term incentives to maintain compliance. Relatively little is known experimentally about how hyperbolic and exponential discounters will discount short and longer term financial penalties and whether novel instruments could be designed to make use of financial penalties as well as incentives in health policy.

Second, a further investigation of four mixture models indicates that *General-hyperbolic* has the best fit to our empirical data, a conclusion which is in contrast with existing practices that predominantly assume *Mazur* or *Quasi-hyperbolic* functional forms. The discrimination among the hyperbolic discounting forms may be a useful tool in the interpretation of the effects of future interventions that either expose an individual to certain conditioned stimuli (e.g. financial incentives provided in commitment contracts) or that alter discounting-associated unhealthy behaviours. Any delay in incentive payments will decrease their effectiveness, and more so if a target population shows time-inconsistent discounting (Madrian, 2014). In this sense, the timing of proximate incentive payments should be tailored such that more immediate rewards should be provided to the target population with a higher degree of time-inconsistency. This demonstrates the advantage of seeking the best-fit discounting form because each of the functional forms indicates a differentiated degree of time-inconsistency. For instance, the *Generalised-hyperbolic* functional form is indicative of a modest decrease of discounting rate over imminent delays, in contrast with *Quasi-hyperbolic* discounting which indicates a sharp decrease. Furthermore, we also found that the failure to adopt the best-fit functional form lead to significantly different discount rates and misleading associations between time preference and smoking status. Researchers should justify their choices of the functional form which fits the data best before any inferences can be made.

In general, these conclusions are pertinent when it comes to designing financial incentives for stimulating behaviour change which is becoming increasingly popular among policy makers, particularly because the evidence for the effectiveness of financial incentives is mixed. Critics argue that financial incentives are crowding out of intrinsic motivation so that they may stimulate behaviour change in the short run but incentivized individuals tend to relapse to old unhealthy behaviours once the incentives are removed, whereas supporters believe that financial incentives assist habit formation (Charness & Gneezy, 2009). In fact, the ineffectiveness of financial incentives may be partly attributed to the failure to have an optimum level of incentive, which we argue should be devised based on the level of impatience and time-inconsistency of the interested samples. One should note, however, that incentivized real-stake experiments are preferable as they offer the potential to deal better with hypothetical bias. In addition, some other instruments, such as contingent valuation, which is a useful tool to elicit willingness to accept financial incentives for behavioural change, should be coupled with discount rate analysis, to develop the optimum level of incentives for intervention programs.

Further, our participants were found to have under-weighted small probabilities and had over-weighted large probabilities, which casts light on the fact that that some people may continue their unhealthy behaviours perhaps because they are "optimistic" about not developing a low probability disease. Although smokers did not display a different probability weighting function in our study, future studies should extend this analysis and investigate how the probability weighting phenomenon helps understand the mechanism by which people perceive rare health events. For example, in the context of smoking cessation, they may have an improper understanding of their cancer risk (in fact, although the risk is lower after quitting, smokers carry a higher risk than non-smokers for years). Health promotion programmes may need to make smokers more aware of the real probabilities of illness attendant on their habit. On the other hand, smokers are likely to underestimate the probability (to be pessimistic) of reaping likely future health benefits (if they were to quit).

A possible drawback of our study is that it does not take into account the functions accommodating increasing impatience, which is another type of violation of constant discounting worthy more attention (Abdellaoui et al., 2010; Abdellaoui et al., 2013). More empirical evidence in this regard is needed as is research to shed light on the public health implications of tailoring intervention to individuals characterised by increasing patience. One should also note that even the best-fit functional form, i.e. *General-hyperbolic*, does not capture a complete picture of discounting behaviours. Instead, a fraction of intertemporal choices, though small, can still be fitted to other functional forms. Thus, another previously overlooked area, but nonetheless an important methodological issue, is the use of a non-parametric method, known as Area Under the Curve (Myerson, Green, & Warusawitharana, 2001) which sums the areas of the trapezoids formed by plotting successive future delays and their associated discount rates inferred by observing indifference points. New avenues are open for future research to compare the performance of parametric and non-parametric methods. Additionally, our study used a cross-sectional dataset which does not allow us to test how time preference interacts with the change of smoking behaviour in a dynamic way. It is also unclear how behavioural change will respond to incentive levels developed by time preference analysis. Future studies should target these areas.

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Figure 1 Proportion of participants choosing Option B

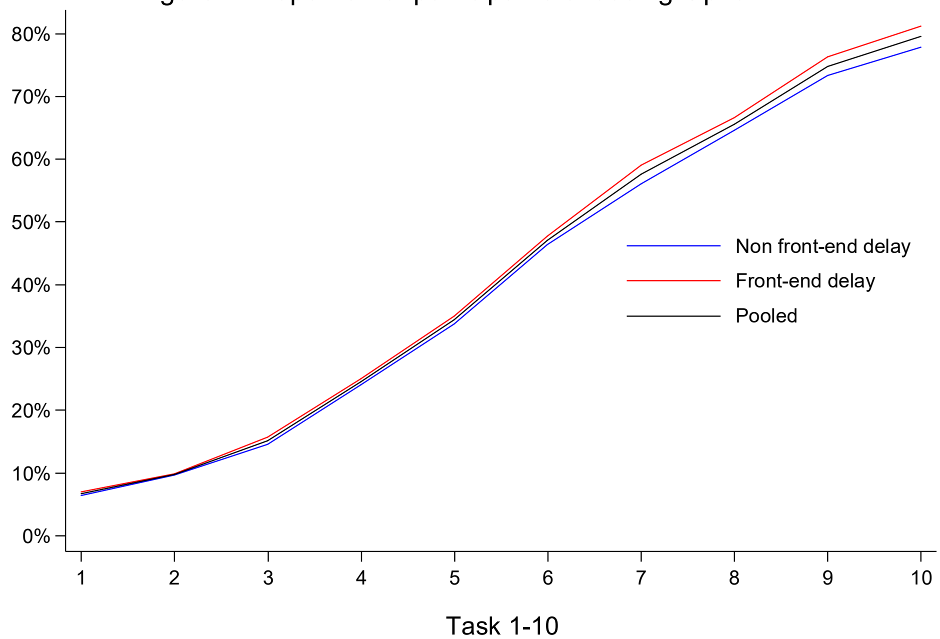

Table 1 Estimated shape parameters assuming an individual functional form

	Sole-parameter functional forms				Dual-parameter functional forms					
	Exponential		*Mazur*		*Weibull*		*Quasi-hyperbolic*		*General-hyperbolic*	
	Estimates	p-values	Estimates	p-values	Estimates	p-values	Estimates	p-values	Estimates	p-values
δ^{E}	0.20(0.03)***	0.00								
δ^{M}			0.27(0.05)***	0.00						
δ^{WB}					0.14(0.02)***	0.00				
β^{WB}					1.29(0.04)***	0.00				
δ^{QH}							0.18(0.03)***	0.00		
β^{QH}							0.993(0.002)***	0.00		
δ^{GH}									0.25(0.05)***	0.00
β^{GH}									3.25(0.57)***	0.00
r	0.57(0.13)***	0.00	0.26(0.16)	0.12	0.67(0.14)***	0.00	0.60(0.13)***	0.00	0.71(0.15)***	0.00
η	0.97(0.11)***	0.00	0.73(0.12)***	0.00	1.06(0.12)***	0.00	1.00(0.12)***	0.00	1.10(0.13)***	0.00
φ	2.48(0.31)***	0.00	2.45(0.34)***	0.00	2.47(0.31)***	0.00	2.48(0.31)***	0.00	2.46(0.31)***	0.00
μ_D	0.38(0.27)	0.17	2.18(1.97)	0.27	0.22(0.17)	0.20	0.31(0.23)	0.18	0.17(0.14)	0.22
μ_R	0.18(0.02)***	0.00	0.17(0.02)***	0.00	0.18(0.02)***	0.00	0.18(0.02)***	0.00	0.18(0.02)***	0.00
No. observations	12320		12320		12320		12320		12320	
No. subjects	176		176		176		176		176	
No. parameters	6		6		7		7		7	
AIC	13033.66		12983.18		12857.56		12958.72		12793.30	
Log-likelihood	-6510.83		-6485.59		-6421.78		-6472.36		-6389.65	

Note: Coefficients are marginal effects. Standard errors (in parentheses) are clustered at the individual level. ***p<0.01, **p<0.05, *p<0.1.

Figure 2 Estimated probability weighting functions

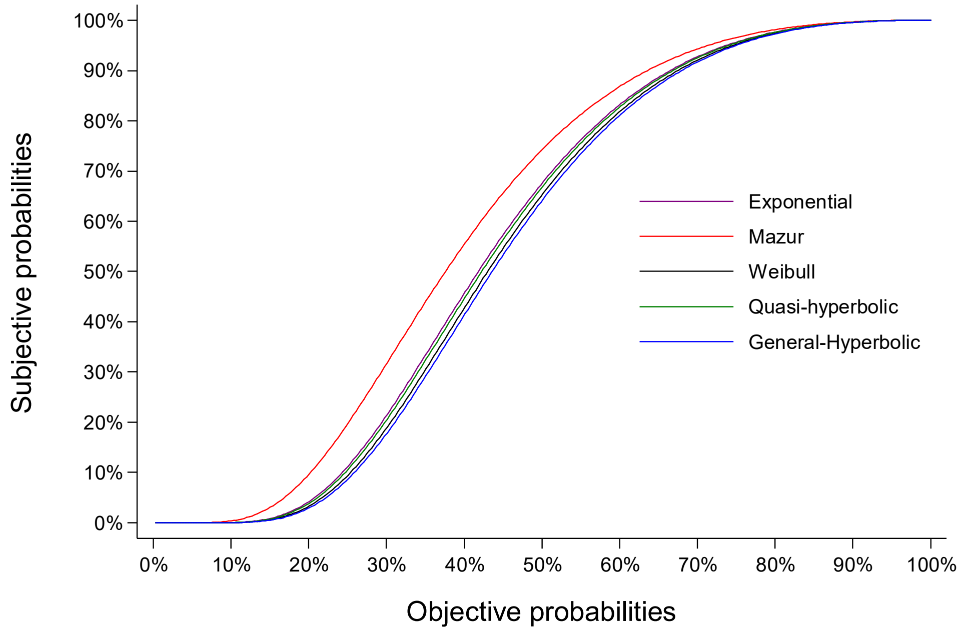

Figure 3 Estimated discount rates over time

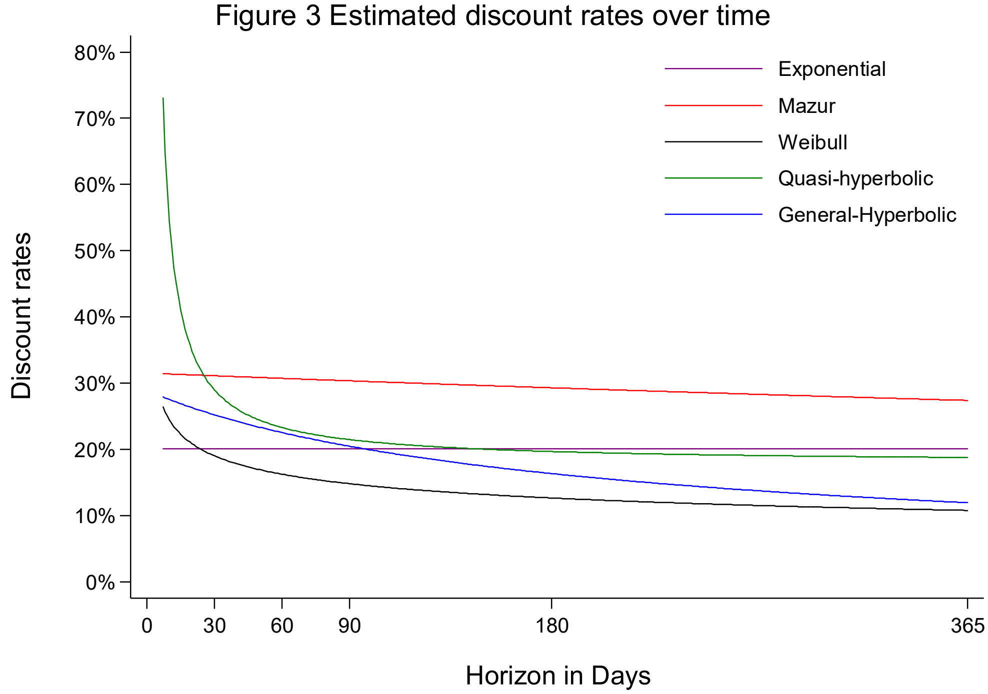

Table 2 Estimated shape parameters in the mixture models

	General-hyperbolic vs. *Exponential*		*General-hyperbolic vs. Mazur*		*General-hyperbolic vs. Weibull*		*General-hyperbolic vs. Quasi-hyperbolic*	
	Estimates	p-values	Estimates	p-values	Estimates	p-values	Estimates	p-values
δ^{GH}	0.32(0.06)***	0.00	0.28(0.05)***	0.00	0.30(0.05)***	0.00	0.31(0.06)***	0.00
β^{GH}	4.48(0.72)***	0.00	3.91(0.74)***	0.00	3.50(0.71)***	0.00	4.34(0.74)***	0.00
δ^{E}	0.17(0.03)***	0.00						
δ^{M}			0.37(0.05)***	0.00				
δ^{WB}					0.13(0.02)***	0.00		
β^{WB}					1.29(0.04)***	0.00		
δ^{QH}							0.34(0.06)***	0.00
β^{QH}							0.998(0.003)***	0.00
r	0.64(0.13)***	0.00	0.48(0.12)***	0.00	0.63(0.13)***	0.00	0.65(0.13)***	0.00
η	1.04(0.12)***	0.00	0.90(0.11)***	0.00	1.03(0.12)***	0.00	1.04(0.11)***	0.00
φ	2.47(0.31)***	0.00	2.48(0.31)***	0.00	2.48(0.31)***	0.00	2.47(0.31)***	0.00
π(*General-hyperbolic*)	0.84(0.04)***	0.00	0.76(0.03)***	0.00	0.77(0.06)***	0.00	0.81(0.07)***	0.00
π(*Exponential*)	0.16(0.04)***	0.00						
π(*Mazur*)			0.24(0.03)***	0.00				
π(*Weibull*)					0.23(0.06)***	0.00		
π(*Quasi-hyperbolic*)							0.19(0.07)***	0.01
μ_{D1}	0.29(0.21)	0.24	0.43(0.28)	0.13	0.34(0.25)	0.18	0.29(0.22)	0.18
μ_{D2}	0.02(0.02)	0.17	0.11(0.07)	0.11	0.04(0.03)	0.27	0.03(0.03)	0.36
μ_{R}	0.18(0.02)***	0.00	0.18(0.02)***	0.00	0.18(0.02)***	0.00	0.18(0.02)***	0.00
No. observations	12320		12320		12320		12320	
No. subjects	176		176		176		176	
No. parameters	11		11		12		12	
Log-likelihood	-6366.09		-6274.97		-6353.64		-6365.00	

Note: Coefficients are marginal effects. Standard errors (in parentheses) are clustered at the individual level. ***p<0.01, **p<0.05, *p<0.1.

Table 3 Robustness checks

Parameter	Assuming risk neutrality	Days over which subjects spend earnings (days=7)	Re-weighting responses to the risk tasks
General-hyperbolic vs. *Exponential*			
π(*General-hyperbolic*)	0.83 (0.04)	0.68 (0.13)	0.83 (0.04)
π(*Exponential*)	0.17 (0.04)	0.32 (0.13)	0.17 (0.04)
General-hyperbolic vs. Mazur			
π(*General-hyperbolic*)	0.79 (0.06)	0.76 (0.03)	0.76 (0.03)
π(*Mazur*)	0.21 (0.06)	0.24 (0.03)	0.24 (0.03)
General-hyperbolic vs. Weibull			
π(*General-hyperbolic*)	0.76 (0.05)	0.72 (0.08)	0.77 (0.06)
π(*Weibull*)	0.24 (0.05)	0.28 (0.08)	0.23 (0.06)
General-hyperbolic vs. Quasi-hyperbolic			
π(*General-hyperbolic*)	0.67 (0.08)	0.81 (0.03)	0.81 (0.07)
π(*Quasi-hyperbolic*)	0.33 (0.08)	0.19 (0.03)	0.19 (0.07)

Notes: Standard errors (in parentheses) are clustered at the individual level. To save space, the estimates for the other shape parameters and the error terms are not reported here but are available upon request.

Table 4 Estimates of the effects of smoking status on shape parameters

	Sole-parameter functional forms				Dual-parameter functional forms					
	Exponential		*Mazur*		*Weibull*		*Quasi-hyperbolic*		*General-hyperbolic*	
	Coefficients	p-values	Coefficients	p-values	Coefficients	p-values	Coefficients	p-values	Coefficients	p-values
Parameters	δ^{E}		δ^{M}		δ^{WB}		δ^{QH}		δ^{GH}	
Smokers	0.04(0.03)	0.15	0.05(0.03)	0.14	0.02(0.02)	0.26	0.03(0.03)	0.25	0.09(0.05)*	0.09
Ex-smokers	0.05(0.03)*	0.06	0.06(0.03)*	0.07	0.03(0.02)**	0.07	0.05(0.03)**	0.04	0.04(0.04)	0.38
Constant	0.20(0.03)***	0.00	0.28(0.05)***	0.00	0.19(0.02)***	0.00	0.18(0.03)***	0.00	0.24(0.05)***	0.00
Parameters					β^{WB}		β^{QH}		β^{GH}	
Smokers	---	---	---	---	0.09(0.12)	0.43	-0.003(0.004)	0.43	1.44(1.65)	0.38
Ex-smokers	---	---	---	---	-0.07(0.09)	0.47	-0.004(0.004)	0.31	-0.36(1.17)	0.76
Constant	---	---	---	---	1.30(0.05)***	0.00	0.993(0.002)***	0.00	3.046(0.735)***	0.00
Parameters	r		r		r		r		r	
Smokers	-0.03(0.03)	0.31	-0.03(0.03)	0.27	-0.03(0.03)	0.27	-0.03(0.03)	0.31	-0.03(0.03)	0.24
Ex-smokers	-0.07(0.03)**	0.04	-0.07(0.03)**	0.04	-0.07(0.04)**	0.05	-0.07(0.03)**	0.05	-0.07(0.04)**	0.05
Constant	0.55(0.13)***	0.00	0.21(0.17)**	0.03	0.65(0.14)***	0.00	0.58(0.13)***	0.00	0.69(0.14)***	0.00
Parameters	η		η		η		η		η	
Smokers	0.19(0.31)	0.54	0.13(0.22)	0.54	0.21(0.34)	0.55	0.20(0.32)	0.54	0.21(0.36)	0.55
Ex-smokers	0.58(0.33)*	0.08	0.49(0.27)*	0.07	0.60(0.35)*	0.08	0.59(0.33)*	0.08	0.61(0.36)*	0.09
Constant	0.86(0.12)***	0.00	0.63(0.11)***	0.00	0.93(0.13)***	0.00	0.88(0.12)***	0.00	0.97(0.13)***	0.00
Parameters	φ		φ		φ		φ		φ	
Smokers	-0.38(0.61)	0.53	-0.36(0.59)	0.55	-0.36(0.62)	0.56	-0.37(0.61)	0.54	-0.35(0.63)	0.58
Ex-smokers	0.77(1.45)	0.77	1.44(2.29)	0.53	0.64(1.31)	0.63	0.72(1.39)	0.61	0.589(1.25)	0.64
Constant	2.47(0.36)***	0.00	2.41(0.46)***	0.00	2.46(0.35)***	0.00	2.47(0.35)***	0.00	2.45(0.35)***	0.00
μ_D	0.45(0.32)	0.16	2.97(2.76)	0.28	0.26(0.20)	0.19	0.37(0.27)	0.17	0.20(0.16)	0.21
μ_R	0.18(0.02)***	0.00	0.17(0.02)***	0.00	0.18(0.08)***	0.00	0.18(0.02)***	0.00	0.18(0.02)***	0.00
No. observations	12320		12320		12320		12320		12320	
No. subjects	176		176		176		176		176	
No. parameters	14		14		17		17		17	
Log-likelihood	-6466.34		-6438.27		-6373.45		-6426.46		-6338.07	

Notes: Coefficients are marginal effects. Standard errors (in parentheses) are clustered at the individual level. ***p<0.01, **p<0.05, *p<0.1.

Figure 4: Estimated discount rates over time